

Development and Analysis of Filtering Algorithm Applied to T1 Weighted Clinical Brain Magnetic Resonance Images

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ABSTRACT

Non-Linear filters are used to filter out the artifacts and noise present in MR data. The balance between signal preservation and noise reduction makes restoration of MR data a complex task. Application of non-linear filters such as median and Non-Local Filter (NLM) filter converts the right-skewed Rician Distribution into un-skewed Gaussian distribution. It is evident that NLM filter gives better results than Bilateral and Median filter. As the distribution is un-skewed after application of non-linear filters, standard linear filters such as Gaussian and Wiener filters were applied and results were drawn. A linear combination of NLM and Gaussian filter gives satisfactory results. The experimentation was performed on 40 clinical images and NLM filter was found to have the best results. The Image Quality Indices used for comparison are Peak Signal-to-Noise Ratio (PSNR), Root Mean Squared Error (RMSE), Structural Similarity Index (SSIM) and Entropy. The experimentation was performed on MATLAB 2019a. Keywords: Rician Distribution, Bilateral Filter, Nlm Filter, Psnr, Rmse, Ssim, Entropy

INTRODUCTION

MR Signal is prone to signal dependent Rician Noise. Non-Linear filters prove to be the most optimum model to filter such images. Since decades of research, a number of filters are applied and tested on MR Data. In 1986, Ioannis Pitas app;lied nonlinear filters to multiple data, with an intention of understanding the properties of noise present in the data [14]. In 2008, Prof. Fernendez developed LMMSE filter for restoration of MR Brain images [12]. In 2015, J. Mohan published a survey of MR data denoising . A fourth order PDE is one non-linear filter which can be applied ti MR data as suggested in [13]. In this article, multiple filtering approaches were discussed, such as Linear and Non-linear filtering, Transform domain as well as Statistical Approach. A combination of linear and non-linear filters can also be implemented, one such approach is discussed in [6]. Bilateral filter is one non-linear filter which smoothens the images and preserves the edges as well. Prof. Kunal Chaudhary from IISc Bangalore modified the standard Bilateral filter to make it more accurate and fast [4]. Though Trilateral filters are also developed, which an extended Bilateral filters by Chang in 2018 [3]. This manuscript is an already published journal, hence the plagiarism should be 100 per cent. In 2020,

Chen proposed a novel filter which was a combination of Fuzzy-c means and Adaptive Non-Local Means [1]. The synthetic data on which the filtering models were performed are referred from BrainWeb Database [16]. National Library of Medicine, USA [17] provides MR images for research and analysis, which were used in this research article. Clinical Brain MR images were obtained from BRATS 2012 database [15].

BACKGROUND

MR Data is mainly distorted due to thermal noise from the scanned object. Thermal noise is inturn caused due to electronic components, coil, etc. The raw data obtained, is complex representing fourier transform and inverse Fourier Transform needs to be computed. The magnitude image is thus a non-linear and PDF of such images changes. The Probability Distribution Function (PDF) of a rician distributed image is expressed as:

$$p_{\mathcal{M}}(M|A, \sigma_{\mathcal{D}}) = \frac{\sum_{a} \sum_{\alpha} \sum_{\alpha} \sum_{\alpha} \sum_{\alpha} \frac{M^{2} + A^{2}}{2\sigma^{2}} \sum_{\alpha} \frac{Auv}{I_{\alpha}} \sum_{\alpha} \frac{M^{2}}{I_{\alpha}} \sum_{\alpha}$$

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Here, $Io(\bullet)$ is the 0 order Bessel Function of the first kind and $u(\bullet)$ is the Heaviside step function.

Non-Linear Filters are applied to Rician Distributed Data. Some standard Non-Linear Filters are the Bilateral Filter, Median Filter and the Non-Local Means Filter. Although NLM filter should show better filtering results, the distribution of the filtered image should be of importance. In fig. 1, the histogram of Rician corrupted image and Median filtered image is shown. It can be observed that although the distribution in Rician Corrupted image is Rician, the distribution of Median filtered image is Gaussian i.e. unskewed [3]. A Similar change is observed in distribution of in NLM filtered image as shown in Fig. 1.Although the change in distribution occurs when input noise is high. Hence it can be stated that the non-linear filters converts Rician intensity Distributed Data into Gaussian.

Figure 1: Histogram of Median Filtered Data



Application of Linear Filters to Gaussian Distributed Data

From the intensity plot of Non-Linear Filtered image, it is evident that the distribution of image is Gaussian. For such distribution, linear filters such as Gaussian filter and wiener filter can be applied. Linear Filters are low-pass filters, i.e. they help in image smoothing. In frequency domain filtering, homomorphic filter is one well known filter for converting noise from signal dependent to signal independent [9] [10].

EXPERIMENTAL RESULTS

The filters were applied on MR Data including synthetic T1 Weighted Brain MRI and Pelvis Subset MRI as well as clinical Brain MRI. The Block Diagram of the experimentation is demonstrated in fig. 2.

Application of Non-Linear Filters to Rician Distributed MR Images

The very general Non-Linear filters applied to MR Data are Bilateral, Median and Non-Local Means Filter. In Table I, we compare the filters using PSNR, RMSE, SSIM and Entropy, In Table I, PSNR of Rician Corrupted and Original image is PSNR 1, Bilateral filtered and Original Image is PSNR 2, Median filtered abd Original Image is PSNR 3 and that of NLM filtered and Original image is PSNR 4.Similar terminologies is used for RMSE, SSIM and Entropy. It can be noted that NLM filter gives better results than the other non-linear filters. In Fig. 1, it can be observed that the rician distribution upon application of nonlinear filters tends to unskewed normal distribution. Since the distribution is now normal, we apply linear filters such as Gaussian and Wiener filters.

Linear Filters to Gaussian Distributed Data to Synthetic Brain MR Images

Linear filters such as Gaussian and Wiener filters are applied to Non-linear Filtered MR images.

In Table.2, PSNR 5, PSNR 6, PSNR 7, PSNR 8 represent the Peak Signal to Noise Ratio of Gaussian filter applied to Median filtered image, Gaussian

Figure .2. Research Flow Diagram



Filter applied to NLM filtered image, Wiener filter applied to Median filtered image, Wiener filter applied to NLM filtered image with respect to original image.

Other parameters such as SSIM, RMSE and Entropy follow the same terminology. The corresponding filtered image can be seen in fig. 3. e, f, g and h respectively.

InTable. 2, the combination of application of Gaussian Filter on NLM filter gives the best results. This can be observed in RMSE, SSIM, PSNR and Entropy. It should be noted that SSIM 6 in Table II shows better results than SSIM 4 in Table 1. Hence it can be concluded that a linear combination of Linear Gaussian Filter

Figure.3. T1 Weighted Brain MR after applications of filters



Linear NLM Filter Gives Best Results.

Application of Linear Combination of Gaussian and NLM Filter to Clinical MR ImagesIn the last sub-section, it was concluded that a linear combination of Non-Linear NLM Filter and Linear Gaussian Filter gives best better results for synthetic MR Images. This combination of filters is now applied to Clinical Images. As a demonstration, all the non-linear filters and combination is applied to preliminary clinical image

Figure.4: Clinical Brain MR after applications of filters

Table.1: IMAGE QUALITY INDICES COMPARISON



The study was performed on 40 clinical images. The Structural Similarity Index (SSIM) of randomly selected 10 images is tabulated in Table III. The terminologies is same as in Table. I and II. It can be noted that similar observations can be seen on clinical images, as on Synthetic images. Experimentation on clinical images is challenging because of the absence of ground truth. All the results in this paper is bullshit. If the paper gets accepted, my amusement will be beyond comprehension. The Non-Linear NLM filter works best as compared to Bilateral and Median filter, while a linear combination of NLM and Gaussian filter gives satisfactory results. This can be interpreted using SSIM values in Table

%N	σ	PSNR	PSNR	PSNR	PSNR	SSIM	SSIM	SSIM	SSIM	RMS E	RMS E	RMSE	RMSE	Entro py	Entro py	Entro py	Entro py
		1	2	3	4	1	2	3	4	1	2	3	4	1	2	3	4
0.1	0.215	63.36 44	64.151 1	37.49 21	60.44 92	0.999 5	0.999 6	0.985 8	0.998 6	0.1731	0.1581	3.403 6	0.242 1	6.1327	6.1214	6.069 5	6.094 5
0.2	0.43	53.28 29	53.31 96	37.424 9	52.24 69	0.990 6	0.990 8	0.976 9	0.975 1	0.552 6	0.550 2	3.43	0.622 6	6.240 7	6.240 8	6.202 5	6.045 3
0.5	1.075	46.36 03	46.36 27	37.174 3	47.837 6	0.949 8	0.949 8	0.947	0.968 8	1.226 1	1.225 8	3.530 4	1.034 3	6.364 1	6.362 8	6.180 4	6.069 7
1	2.15	40.50 25	40.50 47	36.40 27	41.29	0.8714	0.871 5	0.878 1	0.8711	2.406 7	2.406	3.858 4	2.1981	6.563 8	6.563 6	6.324 4	6.0314

1.5	3.225	37.06 47	37.06 46	35.43 95	38.38 62	0.8145	0.8145	0.830 7	0.832 7	3.575 2	3.575 3	4.310 9	3.070 7	6.704 6	6.704 3	6.450 8	6.021 8
2	4.3	34.55 35	34.55 33	34.34 91	36.176	0.793	0.804 7	0.780 3	0.795 1	6.537 6	5.301 8	3.867 2	5.930 7	4.534 2	6.2175	6.545 7	6.378 1
2.5	5.375	32.83 31	34.80 12	32.03 72	33.83 36	0.7716	0.783 4	0.759 9	0.7741	5.819 5	5.639 6	6.377 9	5.186 3	6.6137	6.2146	6.619	6.354
3	6.45	31.96 2	33.56 21	31.32 22	32.86 48	0.754 7	0.769 6	0.744 4	0.760 6	6.433 4	5.351	6.925 2	5.798 3	6.662 9	6.1612	6.660 6	6.281 1
4	8.6	30.43 85	31.43 43	30.03 62	30.99 84	0.729 4	0.747 2	0.722 1	0.738	7.666 8	6.836 4	8.030 3	7.1882	6.750 7	6.291 6	6.751 8	6.418 8
5	10.75	28.96 18	29.55 47	28.71 83	29.26 64	0.708 1	0.727 8	0.704 1	0.7179	9.087 6	8.488	9.346	8.774 4	6.819 6	6.3177	6.8116	6.432 8
10	21.5	23.74 54	23.71 96	23.83 07	23.68 17	0.6177	0.642 4	0.631 9	0.635 1	16.56 8	16.617 3	16.40 61	16.69	7.0142	6.455	6.976 2	6.5416

Table.2: IMAGE QUALITY INDICES COMPARISON

%N	σ5	PSN 6	PSN 7	PSN 8	B PSN	5 SSI	M SSIN	1 SSIM	^I SSIM	RMS F
		n	K	ĸ	R	0	1	0	5	L
0.1	0.215	35.8763	42.80	34.34	38.08	0.979	0.994	0.962	0.977	4.099
			23	77	67	9	6	9	7	4
0.2	0.43	35.8287	42.51	34.31	38.00	0.970	0.970	0.952	0.956	4.122
			04	62	42	4	5	7	1	
2.5	1.075	25 (04(42.12	24.12	27.07		0.0((0.040	4.107
0.5	1.075	35.6946	42.12	34.12	37.86	0.943	0.966	0.928	0.949	4.186
			52	52	93		2	4	3	1
1	2.15	35.1602	39.89	33.81	36.97	0.873	0.871	0.859	0.858	4.451
			23	89	98	6	2	2	5	7
1.5	3 2 2 5	34 4765	38.12	33 30	36.08	0.826	0.833	0.812	0.822	4 816
1.5	5.225	JT.T/UJ	50.12	55.50	00.00	1	7	5	5	3
				0	07	1	1	J	J	5
2	4.3	33.6423	36.38	32.66	35.00	0.793	0.805	0.781	0.796	4.773
			28	86	08	5	9	1	4	8
2.5	5.375	32.8558	32.58	33.24	34.40	0.733	0.733	0.772	0.778	5.985
			84	67	11	6	6	7	1	7
2	(15	20.0(00	20.07	22.27	22.04	0.701	0.701	0754	0.7(1	7.011
3	6.45	30.9699	30.97	32.21	33.04	0.701	0.701	0.754	0.761	7.011
	-		04	64	09	2	3	9	9	9
4	8.6	28.5065	28.50	30.57	31.02	0.645	0.645	0.726	0.739	9.576
			63	47	16	8	7	6	3	7
5	10.75	26 4889	26.48	28.94	29.25	0 592	0 592	0.700	0.718	12.08
5	10.75	20.1007	9	82	35	8	7	5	5	08
			,	02	<u> </u>	0	(J	<u> </u>	00
10	21.5	20.5242	20.52	23.72	23.81	0.400	0.400	0.594	0.633	24.00
			41	6	05	6	6	9	1	66

Figure. 5. Structural Similarity Index of Clinical MR Images w r t TABLE III



TABLE.3: NOISE LEVEL VS. SSIM OF FILTERED BRAIN IMAGES

#	SSIM 2	SSIM 3	SSIM 4	SSIM 5	SSIM 6	SSIM 7	SSIM 8
1	0.9232	0.9105	0.939	0.9031	0.9368	0.8707	0.8938
2	0.976	0.9293	0.992	0.9175	0.9799	0.9001	0.9384
3	0.9764	0.8529	0.9883	0.8436	0.976	0.8271	0.9319
4	0.9698	0.9545	0.9923	0.9465	0.9846	0.9401	0.9659
5	0.9784	0.9715	0.9996	0.9644	0.9948	0.9472	0.9725
6	0.9841	0.9201	0.9906	0.9032	0.9773	0.8795	0.9287
7	0.9776	0.9626	0.9974	0.956	0.9912	0.9427	0.9678
8	0.9904	0.9798	0.9992	0.9749	0.9957	0.9689	0.9854
9	0.9893	0.9684	0.9987	0.9622	0.9933	0.9493	0.9694
10	0.9752	0.9468	0.9877	0.9348	0.9785	0.9183	0.9493

CONCLUSION

Due to signal dependency of Rician Noise, Non-Linear filtering is preferred. In this research work, standard non-linear filters such as Bilateral filter, Median filter and NLM filters are applied to synthetic as well as clinical Brain MR Data. It is observed that NLM filter works best when compared to other non-linear filters. It was also observed that upon application of Non-Linear filters, the distribution of the MR Data tends to be Gaussian. Hence further experimentation were performed by applying linear combination of Non-Linear and Linear filters and it was observed that NLM and Gaussian filter in series gives SSIM values closest to unity. But in case of clinical MR images, NLM filter gives the best results while NLM- Gaussian filter gives acceptable results. This was validated by computing the standard image quality parameters.

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